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A smartphone based real-time daily activity monitoring system

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Abstract A real-time activity monitoring system within an Android based smartphone is proposed and evaluated. Motion and motionless postures may be classified using principles of kinematical theory, which underpins hierarchical rule-based algorithms, based on accelerometer and orientation data. Falls detection was implemented by analyzing whether the postures classified as 'lying' or 'sit-tilted' posture are deemed normal or abnormal, based on the analysis of time, users' current position and posture transition. Experimental results demonstrate that the approach can detect various types of falls efficiently (i.e., in real-time within a smart phone processor) and also correctly (95 % and 93 % true positives for falls ending with 'lying' and 'sit-tilted' respectively). The approach is reliable for different subjects and different situations, since it is not only based on empirical thresholds and subject-based training models, but in addition it is underpinned by theory.

Keywords Posture classification · Falls detection · Backward reasoning · Smartphone · Real-time processing

1 Introduction

Automatic monitoring of daily activities can be used to encourage people to lead a healthier lifestyle, for example, to promote regular exercise or maintain healthy postures, and can also assist elderly people living independently at home. Therefore, daily activity monitoring with context-aware reminders/alert delivery has the potential to reduce the occurrence of chronic diseases and supply significant savings in future healthcare costs especially for elderly people or those suffering from a form of chronic disease.

Pervasive computing utilizes a large number of tiny computers equipped with sensors that can communicate with our living environment. Augusto et al. [1] discussed the basic features of intelligent environments. Pervasive computing requires applications that are able to operate in highly dynamic environments and require minimal information from and interaction with users. Context-aware applications can meet these requirements by automatically adapting to acquired context, such as location, environmental conditions, and current activity. Howard & Cambria [2] discussed that intention-aware based systems offer an advantage over situation-aware based systems in that they reduce this information burden.

Falls are the leading cause of injury and a major global health problem, particularly for the elderly population and those who are suffering from chronic disease. For example, people with chronic heart failure or stroke may suffer a form of abnormal heart rate and/or gait disorders; these symptoms lead to the increased risk of falling during their daily activities. Approximately 3 % of all persons who experience a fall will remain on the ground or floor for more than 20 minutes prior to receiving assistance [3]. Reliable and timely detection of the fall is therefore important to ensure that the person may receive assistance as necessary.

This research developed a smart phone based activity monitoring system to classify motion and motionless daily activities, enabling us to distinguish falls in various situations.

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The remainder of the paper is organized as follows. The related work is discussed in Sect. 2. Methodologies for the system configuration and activity classification algorithms are described in Sect. 3. The experimental protocols and the experimental results are presented in Sect. 4. Finally, Sect. 5 focuses on the discussion, conclusion and the future work.

2 Related work

Classification of human activities of daily living (ADLs) involves several tasks: data sensing, feature extraction, and activity classification.

Many studies have been focused on daily activity classification along with falls detection by using different devices such as environment-embedded sensors and wearable sensors. Sensors, e.g. cameras, can be embedded in a tracking environment; however, they can only monitor fixed places and there are privacy-protection issues to resolve, for complete coverage, e.g. in the bathroom. Wearable sensors such as gyroscopes, tilt sensors and accelerometers are more flexible, allowing users to be monitored both within and outside of their home environment [4].

Feature extraction aims to describe human ADLs using appropriate measures of activity discrimination (such as spectral entropy or acceleration). The features are selected for each activity by identifying one feature having the best performance that distinguishes the required activity from other activities. Features may either use the raw sensing data directly or by performing calculations on the raw sensing data. Many feature extraction techniques have been used for activity classification; Györbíró et al. [5] discussed the use of Fast Fourier Transform (FFT), Principal Component Analysis (PCA), and Independent Component Analysis (ICA) for pre-processing of data.

Classification aims to assign a class label to each of the instances in a data set based on the values of the features using a trained model (classifier). A large number of machine learning algorithms have been developed for model training and testing. The choice of machine learning algorithm for a classification problem is normally decided based on classification results. Commonly, a classifier's performance is evaluated using its prediction accuracy and computational efficiency. The best-known algorithms in the literature for activity classification are Support Vector Machine (SVM), Naïve Bayes (NB), C4.5 Decision Trees (DT), k-Nearest Neighbour (kNN), Neural Networks, and Rule-based algorithms [6]. For example, Yang [7] performed activity recognition using mobile phones with built-in accelerometers. Six daily activities: sitting, standing, walking, running, driving and cycling were classified and the comparison based on features such as mean and standard deviation acceleration magnitudes, as well as the separate vertical and horizontal components. They evaluated and compared four classifiers, namely C4.5, DT, NB, kNN and LibSVM, using the 10-fold cross-validation method. Their experimental results showed that a well-pruned DT model achieved the best performance with acceptable computational complexity. kNN and SVM achieved good classification performance based on the selected magnitude features, but at cost of increased computational time. The computational efficiency of feature extraction is particularly important for a mobile of processor in a smart phone, which is less powerful than a conventional computer, although the performance gap is narrowing.

Namsrai et al. [8] proposed a method to build an ensemble of classifiers by using a feature selection schema (FSS) for analyzing the electrocardiogram. The FSS identifies the best feature sets that affect the arrhythmia classification. In their method, a number of classification models were built based on each feature subset, and the classifiers were combined by adopting a voting approach to form a classification ensemble. Experimental results illustrated that this method can improve the classification accuracy in high dimensional datasets. Oh [9] introduced an additive training method to construct a search tree for predicting the user's location based on the past movement patterns.

There are commercial products used for falls detection and alert notification. For example, MCT-241MD PERS [10] is a commercial fall detector consisting of a built-in tilt sensor and a manual emergency alert button. It can automatically trigger a call to a remote monitoring station for immediate help if a user wearing it tilts at more than a preset angle for more than about a minute. Another product, Medical Alert System [11], can transmit an alert to the monitoring agents when a user presses the button on the pendant to call for help. These kinds of products have been used successfully for emergency monitoring and alert delivery, but are limited to indoor monitoring, due to a dependence on proximity to a land phone line.

Falls are normally characterized by a larger acceleration change compared to the types of measurements associated with normal daily living activities. Hence accelerometers are the most common device used for fall detection, supported by activity classification software. For example, Kangas et al. [12] documented acceleration of falls from sensors attached to the waist, wrist and head. Their experimental results demonstrated that measurements from the waist and head were more useful for the purposes of fall detection. Bourke et al. [13] mounted two tri-axial accelerometers on the trunk and thigh, and derived two thresholds (upper and lower) for each position. Finally, they indicated that the upper threshold gave higher specificity than the lower threshold.

A method, which uses only the accelerometer with some empirical threshold, can lead to many false positives from other 'fall-like' activities such as sitting down quickly and jumping, which also feature a large acceleration change. Chen et al. [14] used the lying posture to detect falls, however limiting the classification to detecting only the lying posture does not work when the user is left in a sitting position after a fall. Machine-learning techniques have also been used for the falls detection [15]. However, the machine-learning algorithm normally has low computational efficiency and it is also difficult to train algorithms for the various fall situations.

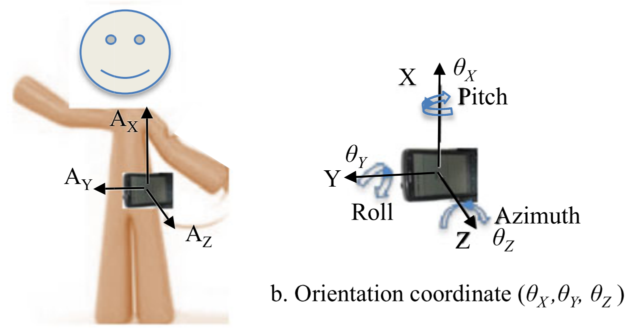
Combining accelerometers with other sensors can improve the reliability of activity classification. Bianchi et al. [16] integrated an accelerometer with a barometric pressure sensor into a wearable device to improve upon existing accelerometer-only approaches. Li et al. [17] proposed a fall detection framework that attached two tri-axial accelerometers with gyroscopes on the chest and thigh respectively, and evaluated that the fall detection accuracy was improved by coupling accelerometers and gyroscopes. Sinha et al. [18] demonstrated a clustering protocol for data aggregation in a wireless sensor network, based on the entropy of the sensors. Their experimental results have shown that the entropy measurement makes more accurate aggregation at the cluster head and performs in an energy efficient manner.

Smart phone based context-aware applications have been widely used in many areas of our daily life. For example, Gallego & Huecas [19] presented a context-aware mobile personalized recommender system based on multiple banking data such as customer profiles, credit card transactions and locations. Werth et al. [20] presented the architecture of an ecosystem of mobile-services generated by users themselves. Tsai et al. [21] developed a trusted M-banking system that can provide secure banking services based on the combination of a one-time password and persona biometric based on mobile phones. Hoang et al. [22] introduced adaptive cross-device gait recognition using accelerometers embedded in a smart phone.

A smartphone based real-time daily activity monitoring with falls detection system is proposed in this paper. Firstly, a hierarchal rule-based algorithm is used to classify the motion and motionless postures respectively; then a rule-based backward reasoning algorithm is used to detect certain categories of falls, possible falls or normal lying. Algorithms developed in this study are based on principles of accelerometer and orientation sensors as well as the kinematical theory, so it is reliable for different subjects and different situations.

3 Methodology

This study developed and evaluated a real-time activity classification along with fall detection system within a HTC (Android operating system) smart phone.



b. Orientation coordinate (θ_X, θ_Y, θ_Z)

a. Accelerometer coordinate (Ax, Ay, Az)

Fig. 1 System configuration; data sets acquired from the phone's sensors: (**a**) acceleration, (**b**) orientation angles

3.1 System configuration

An HTC Wildfire S A510e phone was used for data sensing and processing in this study. This phone includes an embedded BMA150 3D accelerometer, AK8973 3D Magnetic sensor, AK8973 orientation sensor, GPS and Wi-Fi sensors. The phone's processor operates at 600 MHz, the memory capacity is 512 MB with an additional 2 GB memory card and the operating system is Android version 2.3.3. In this study, the phone is belt-worn on the left side of the waist in a horizontal orientation. In this case, the accelerometer coordinate system is that the x-axis is vertical, the y-axis is horizontal and the z-axis is orthogonal to the screen, as shown in Fig. 1(a).

The phone's orientation (or position relative to the magnetic north) can be monitored using the orientation sensor. This sensor provides 3D rotation angles along the three axes (*pitch, roll, azimuth*), denoted as ($\theta_X, \theta_Y, \theta_Z$), as depicted in Fig. 1(b).

Two raw data sets: 3D acceleration (t, A_x, A_y, A_z) and 3D orientation angles $(t, \theta_X, \theta_Y, \theta_Z)$ were obtained at the same time. Subsequently, the two data sets were used for the features extraction as well as evaluation of the posture classification and fall detection algorithms. The recorded data and analyzed results were saved in the phone in a text file.

3.2 The sampling frequency

Signals should be samples at twice the hightest frequency of interest. With the phone it is possible to sample between 5 Hz and 80 Hz. In theory, with a low sampling rate is possible to miss some of the higherfrequency values for motion activities (such as walking). Although the missed higher values can influence the detailed analysis for motion activities, such as walking speed, but it does not influence the classification accuracy for the simpler task of distinguishing motion and motionless postures. A study by Zhang et al. [23] has compared the activity classification accuracy based on data collected from GENEA accelerometer, with sampling frequency ranging from 5 Hz to 80 Hz for the four types of activities: sedentary, household, walking and running. Their experimental results illustrated that the classification accuracy was greater than 95 % irrespectively with the sampling rate at 80 Hz (96.9 % ± 1 %), 40 Hz (97.4 % ± 0.7 %), 20 Hz (96.9 % ± 1.1 %), 10 Hz (97 % ± 1 %) and 5 Hz (95 % ± 1.4 %). Thus higher sampling frequencies were not associated with greater classification accuracy for these daily activities. Lower sampling rates result in a lower data load and higher efficiency of data processing.

Therefore, in order to reduce the data load and improve the performance of the smart phone, the sampling frequency was set at 5 Hz in this study.

3.3 Data sensing

3.3.1 Acceleration

We know that acceleration is a physical characteristic of a subject in motion. An accelerometer is a device that can measure the static acceleration due to gravity, and dynamic acceleration resulting from motion, shock, or vibration [24].

An accelerometer will measure a value of $\pm 1g$ (unit of gravity acceleration, which is 9.81 m/s^2) in the upward or downward direction if it remains stationary relative to the earth's surface. If a tri-axis accelerometer is embedded in a smart phone, six 3D coordinate systems are apparent (vertical axis is X, Y or Z in upward or downward directions) according to the phone's orientations, as shown in the following three cases.

- $A_y = \pm 1g$ when the phone is vertical, the y-axis is vertical in this case;
- $A_x = \pm 1g$ when the phone is horizontal, the x-axis is vertical in this case;
- $A_z = \pm 1g$ when the phone's screen is parallelized with the earth's surface, the z-axis is vertical in this case.

In theory, the vertical-axis value will be $g = \pm 9.81\text{m/s}^2$, and along the other two axes will be 0. In the real world, although the stationary acceleration is difficult to exactly keep the theoretic values 9.81 or 0 along 3-axis, but the absolute value of vertical acceleration is always equal to the maximum stationary value among ($|A_x|$, $|A_y|$, $|A_z|$).

3.3.2 Orientation angles

The orientation sensor provides 3D rotation angles along the three axes (pitch, roll, azimuth), denoted as $(\theta_X, \theta_Y, \theta_Z)$.

- Pitch (θ_X), degrees of rotation around the x-axis, $\theta_X = [-180°, 180°]$, with positive values when the positive z-axis moves toward the positive y-axis. $0° =$ horizontal; $\pm 180° =$ upside down; $\pm 90° =$ left/right.
- Roll (θ_Y), degrees of rotation around the y-axis, $\theta_Y = [-90°, 90°]$. $0° =$ horizontal; $90° =$ upward; $-90° =$ downward.
- Azimuth (θ_Z), degrees of rotation around the z-axis, $\theta_Z = [0°, 360°]$. $0°/360° =$ North; $180° =$ South; $90° =$ East; $270° =$ West.

According to the definition of the $(\theta_X, \theta_Y, \theta_Z)$ above, the three angles will vary according to the specific body postures. Especially, the angle θ_Z can be used as a compass, and the angles of (θ_X, θ_Y) can be used to recognize the upright and tilted postures.

3.4 Posture classification

The high level contexts of activity posture and the body orientation are classified at the same time, using hierarchal rule-based algorithms, based on integrated data set (it includes raw data and extracted features) such as $(t, id, A_x, A_y, A_z, \Delta A,\ \theta_X, \theta_Y, \theta_Z)$. Where t is the time stamp, id is the calculated sample number, Δ_A is the calculated acceleration change.

3.4.1 Motionless postures classification

On a general level, human daily activities can be divided into motion and motionlessness. If a subject is motionless, his/her acceleration and velocity should, in theory, be zero. Nevertheless, the signal measured by an accelerometer in practice always contains some noise and is therefore usually never exactly zero. Accordingly, the motionless features were defined by the changes of three dimensional acceleration (ΔA) and the period of motionless time. The three-dimensional acceleration A_{xyz} can be calculated by sensed data (A_x, A_y, A_z) as shown in Eq. (1). Then the ΔA is calculated using $Axyz$, as shown in Eq. (2).

$$A_{xyz} = \sqrt{A_x^2 + A_y^2 + A_z^2} \tag{1}$$

$$\Delta A = \left| A_{xyz}(t_{i+1}) - A_{xyz}(t_i) \right| \tag{2}$$

In this study, the motion and motionless postures are classified using a hierarchal rule-based algorithm. First, a motionless rule R_{ml} as shown in Eq. (3) and (4) was used to separate the motion and motionless postures into two arrays; then the motionless postures (lying, sit, stand, sit-tilted and stand-tilted) were classified by combined lying rule R_{lyi} as shown in Eq. (5) and (6) and a tilted rule R_{til}. The details of three rules (R_{ml}, R_{lyi}, *and* R_{til}) are described as below.

$$R_{ml} = \begin{cases} \forall [t_m, \mathrm{t}_l] \in T_{ml}; \quad T_{ml} \geq mlp & (3) \\ |\Delta A| \leq th1 & (4) \end{cases}$$

where the motionless period of time T_{ml} is for more than a predefined period of time mlp (such as $mlp = 2$ s), which provides appropriate details and reduces the posture fragments for long term daily activity monitoring; the value $th1 = 0.4$ m/s^2 was determined based on kinematical theory and empirical data, as described in Experiments section.

R_{lyi}: During a motionless period of time T_{ml}, if the maximum absolute value among $(|A_x|, |A_y|, |A_z|)$ is not Ax, and it approximately equal to g as expressed in Eqs. (5) and (6), then the motionless posture must be lying. This lying rule is established based on the accelerometer principles.

$$R_{lyi} = \begin{cases} A_{\max} = \mathrm{Max}(|A_x|, |A_y|, |A_z|) \approx g & (5) \\ A_{\max} \neq A_x & (6) \end{cases}$$

$$R_{til} = \begin{cases} if\ (|\theta_x| \geq (0^\circ + \theta_{cali}) \vee |\theta_y| \leq (90^\circ - \theta_{cali})) \\ \{til = upright\} \\ else\{til = tilted\} \end{cases}$$

where the practical value θ_{cali} is used to calibrate the ideal value for θx and θy. Ideally, the θy is around $\pm 90^\circ$ and θx is around 0° when the x-axis is vertical, nevertheless, it is difficult to guarantee that the belt-worn phone keeps ideally vertical when the body posture is upright (such as standing), so a practical value $\theta_{cali} = 20^\circ$ is used to calibrate the ideal value for θx and θy respectively.

The motionless postures were classified as {*lying*, *sit*, *stand*, *sit-tilted*, *stand-tilted*} by combing the rules R_{ml}, R_{lyi}, and R_{til}.

3.4.2 Motion postures classification

It is similar with the motionless definition above, the motion postures also defined as the motion period of time (T_m) is for more than a predefined period of time *mp* (such as $mp = 1$ s), as shown in Eq. (7). This definition can ignore the short periods of motion or slight motion during a motionless period of time.

The motion postures were initially classified as *walk, run, jump*, and *posture transition* (PT) according to the T_m and the ΔA as expressed in the motion rule R_m below.

$$R_m = \begin{cases} \forall [t_{m1}, t_{m2}] \in T_m; \quad T_m \geq mp & (7) \\ if\ (T_m \leq smp)\{pos = (\Delta A \geq th2)?jump : PT\} \\ else\{pos = (\Delta A \geq th2)?run : walk\} \end{cases}$$

where the value of short motion period of time (*smp*) is 2 seconds ($smp = 2$ s) and $th2 = 3.5$ m/s^2 were determined empirically using the collected data, as described in Experiments section.

Combining the above rules R_{ml}, R_{lyi}, R_{il} and R_{m} has the ability to separate the entire signal into several motion and

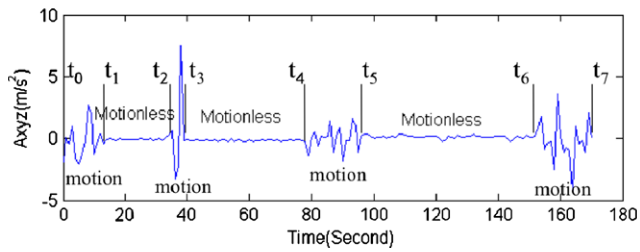


Fig. 2 The data signal is separated into several motion and motionless time sequences

motionless time sequences and saved corresponding classification result in a posture array. For example, the signal shown in Fig. 2 will be expressed as four motion and three motionlessness periods as below, and the posture array saved as

Motion periods: $< t_0, t_1 >; < t_2, t_3 >; < t_4, t_5 > \in T_m$

Motionless periods: $< t_1, t_2 >; < t_3, t_4 >; < t_5, t_6 > \in T_{ml}$

Posture array: $\{pos(t_0), pos(t_1), \ldots, pos(t_7)\}$

3.5 Falls detection analysis

Based on the results of postures and orientation classification, the falls detection was implemented by analyzing whether the current lying or tilted postures are normal or abnormal, based on the falls characteristics and posture transition analysis, using rule-based backward reasoning.

It is well known that the common features for all kinds of falls are that the body results in a lying or sitting tilted posture, however, not all lying or sitting tilted postures are falls. The fall detection rule (R_{fall}) was defined as:

$$R_{fall} = \begin{cases} \forall [t_i, t_{i+1}] \in T_{ml}; \quad if(pos(t_i) \\ \quad \equiv lying || sit - tilted)\{ \\ (pos(t_{i-1}) \equiv walk || run || jump)?fall : \\ (\forall (t_i, t_{i+1}) \in T_{rest})?normal : possible fall\} \end{cases}$$

According to the R_{fall}, a certain fall or a possible fall will be detected in the different situations, as depicted below.

Certain Falls: if a lying or sit-tilted posture was detected during the motionless period of time T_{ml}, at the time t_i, then a backward reasoning algorithm will be used to check the saved previous posture $Pos(t_{i-1})$. If $Pos(t_{i-1}) =$ *walk, run or jump*, then the posture transition is analysed as abnormal, so a certain fall alert will be delivered immediately.

Possible Falls: otherwise, if the $Pos(t_{i-1}) =$ *standing or sitting*, then analyse whether the lying period of time (t_i, t_{i+1}) is within the user's prescheduled rest (such as sleeping or nap) period of time T_{rest}. If so, the current lying will be analysed as normal; if it is not, a possible fall is raised, so a music based alert starts playing, and finally, a fall or a normal lying/sit-tilted will be determined according to whether the user stops the alert music.

The postures and orientations classification were performed point by point in real-time and the sensing data with the classification results saved in a multi-dimensional array as (t, A_x, A_y, A_z, ΔA, θ_X, θy, θ_Z), *posture*, *orientation*, *status*), whilst the abstracted information for the period of maintaining the same posture was saved in another array. Finally, all results were stored in corresponding text files within the phone.

4 Experiments

The proposed activity postures classification along with falls detection system was evaluated at an indoor (a real home) environment in real-time using a HTC smart phone. Six healthy people (5 male and 1 female, age range 20–52 years) simulated various falls and a set of normal daily activities. For the purposes of safety, a mat was put on the ground for the falls experiment.

The experimental results were validated against notes recorded by two independent observers following the experiments. The experimental results, especially the falls detection results were compared to using an accelerometer with a pre-defined threshold method described in our previous work [25]. The two algorithms were named as *PosTra* and *AccThr*, depicted as below.

PosTra: falls were detected based on the integration of posture transition and the current time as well as the user's current position, as proposed in this paper (the position was discussed in our previous work [26]).

AccThr: only using the acceleration change with pre-defined threshold to detect falls, as described in our previous work [25].

4.1 Data sensing

4.1.1 Data sensing and the system interface

The sensed raw data (t, A_x, A_y, A_z, θ_X, θ_Y, θ_Z) with analyzed results (t, *posture*, *location*, *status*) were saved point by point in a text file within the phone in real-time, and displayed on the phone as Fig. 3 shown. A fall alert will be delivered immediately if a fall is detected; additionally, if a possible fall is detected, a music alert will sound and a stop button will appear on the smartphone's screen, waiting for user's response. This allows a user to override an alert situation, which could have been a false positive.

4.1.2 Parameter th1 and th2 determination

The parameter *th1* was used to separate motion and motionless postures in the motionless rule R_{ML}. The parameter

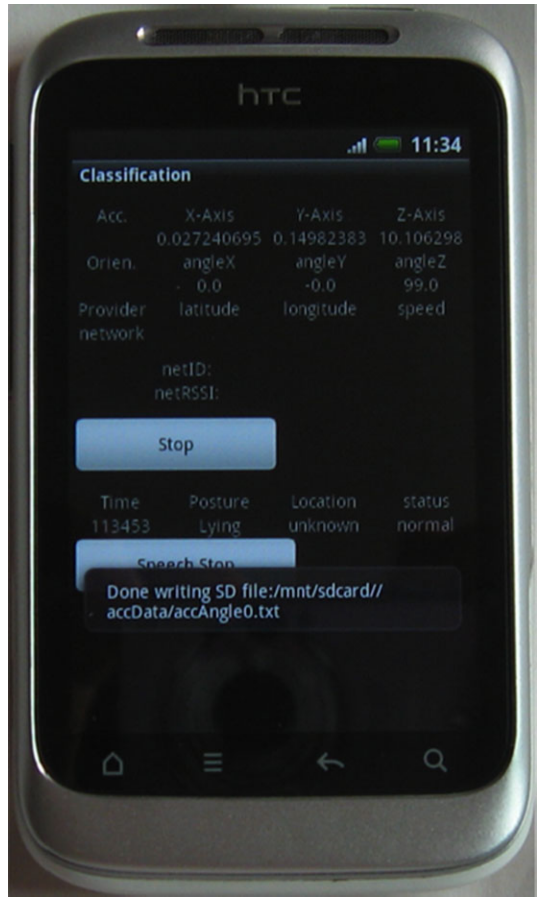


Fig. 3 Interface of the monitoring system on the phone

th2 was used to classify different motion postures in motion rule R_m. Experimental protocol for determining *th1 and th2* value is shown below.

1. Six subjects wore the HTC phone on their waist and carried out three motionless activities of sitting, standing and lying for 1 minute respectively, 900 motionless samples (t, A_x, A_y, A_z) were collected from each subject.
2. Data collected from six subjects were mixed together.
3. Three dimensional acceleration (*Axyz*) and the change of three dimensional acceleration (ΔA) were calculated according to Eq. (1) and Eq. (2).
4. Values of ΔA were sorted from highest to lowest, and the distribution of the ΔA values was analyzed.

The experimental result shows that the ΔA was distributed as: highest value 0.798 m/s^2, six sample values between 0.5 m/s^2 and 0.67 m/s^2, eight sample values between 0.41 m/s^2 and 0.49 m/s^2, and the remaining 98.6 % samples were less than 0.4 m/s^2. Figure 4 shows part of the sorted ΔA samples. Therefore, the motionless postures can be separated from the motion postures correctly by using the motionless rule R_{ML} with proper parameters.

The parameter $th2 = 3.5$ m/s^2 was determined empirically using the collected motion data. The experiments of

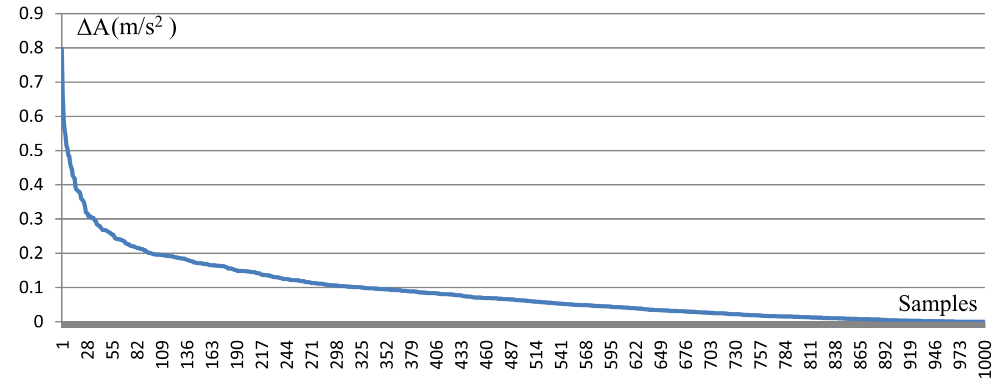


Fig. 4 Sorted motionless ΔA samples

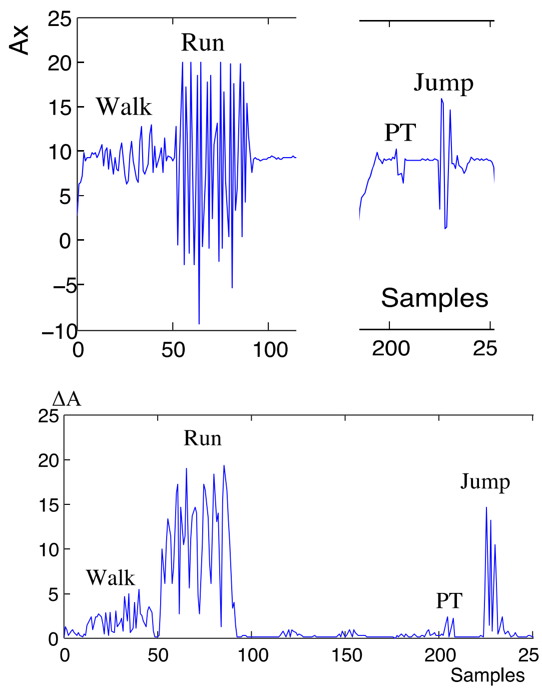


Fig. 5 A_x and ΔA signals for the four motion postures

motion (*walking*, *running*, *jump* and *PT*) data collecting for the *th2* setting was similar to the *th1* approach. Figure 5 shows the part of A_x signal for the four motion postures and corresponding ΔA signal.

4.2 Normal and abnormal daily activities

Each of the 6 subjects performed several series of activities, described below, in a random order and random period of time for 2 times for each of the groups activity postures. On another day, 3 of the 6 subjects performed the same activities in prescript order for another 8 times respectively at a home environment.

4.2.1 Normal daily activities

- Walk → Stand → Run → Stand forward → Jump → Sit on a chair.
- Stand → Sit on bed → Lying on bed → Sit-tilted on bed → Stand → Walk → Jump → Run

4.2.2 Falls and fall-like activities

- *Fall-lying*: falls ending with lying. From walk, run, or jump to lying on the mat covered ground and bed suddenly (quickly).
- *Fall-sitTilted*: falls ending with sit-tilted. From walk, run or jump to sit-tilted on the ground and bed slowly.
- *Normal lying:* From walk to stand or sit and then lying on the bed or sofa slowly in two ways: Sit $\geq$ 2 s before lying; and Sit $<$ 2 s before lying.
- *Bending:* From standing to bending more than 30°.
- *Jump and Sit-heavily:* From Standing to jump and then sitting down heavily on a chair.

Some of the ending postures following a fall from these experiments are shown in Fig. 6. The left single column shows the system configuration that a belt-worn smart phone was used for daily activity monitoring with fall alert delivery; the top of row shows 3 subjects fell down ending with different lying postures on the (mat covered) floor; the bottom row shows another 3 subjects fell down ending with different sitting postures. For privacy protection, images in Fig. 6 have been recolored.

Activities from motion posture (such as walking, running, or jumping) to lying or sit-tilted suddenly are defined as abnormal posture transition, especially for elderly people. Falls should be detected in these cases. For example, Fig. 7 illustrated the comparison of normal and abnormal lying, using the part of acceleration signals from standing to lying slowly (as shown in the top of figure, it is a normal lying), and from walking to lying suddenly (as shown in the bottom of figure, it is a fall).

In addition, although the posture transition from sitting or standing to lying slowly is normal, however if the lying posture is in a wrong place (such as the ground outside, as determined by location detection), or at an implausible time (such as not the scheduled nap or sleeping time), then a possible fall alert should be playing in this case.

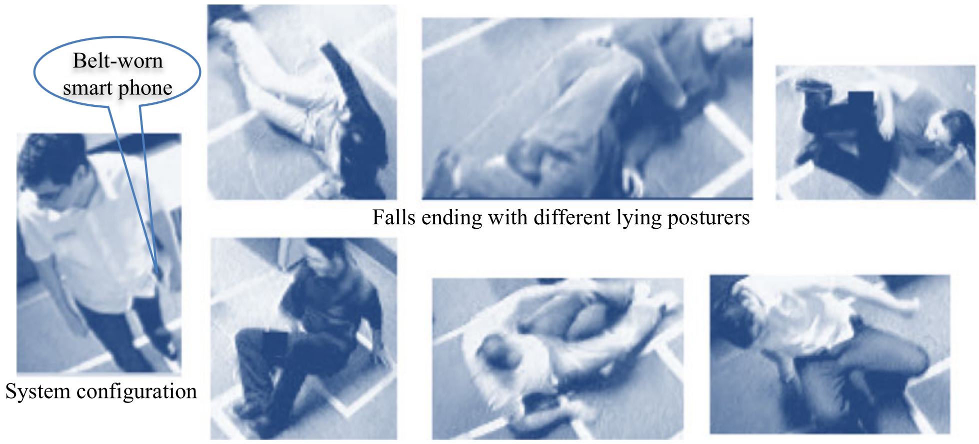


Fig. 6 Falls ending with different postures for different subjects and different situations; (1) the left single column shows the system configuration; (2) the top of row shows 3 subjects fell down ending with different lying postures; (3) the bottom row shows another 3 subjects fell down ending with different sitting postures. Note: in order to protect personal privacy, all images have been recolored

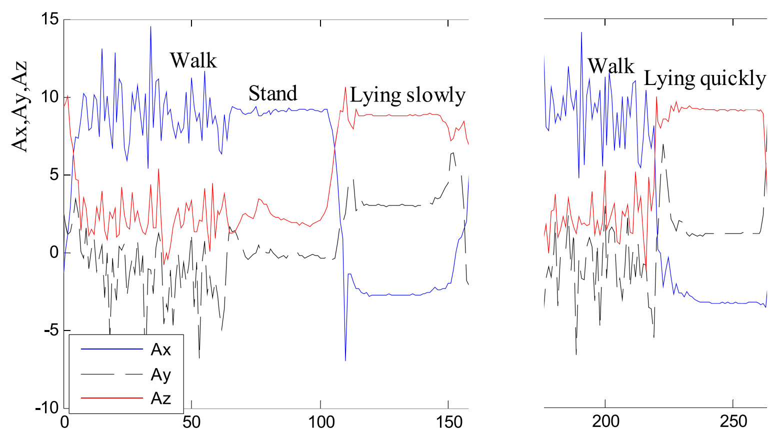


Fig. 7 Comparison of normal and abnormal lying; the top of figure shows the part of acceleration signal from standing to lying slowly; the bottom of figure shows from walking to lying suddenly

4.3 Experimental results

In these experiments, there were 72 ($= 6 \times 2 \times 2 + 3 \times 8 \times 2$) falls ending with lying (Fall-lying, in this case, the acceleration changing is large); 72 falls ending with sitting tilted (Fall-sitTilted, in this case, the acceleration changing is small); 72 normal lying, 36 bending and a number of standing, walking, sitting and fall-like (such as jumping and sitting down heavily) activities recorded in total.

The normal and abnormal daily activities were classified using the two algorithms *PosTra* and *AccThr* respectively. The experimental results (shown in Fig. 8) were compared between both algorithms from 4 aspects:

(1) *True positive*: recognize real falls correctly.
(2) *False negative*: recognize real falls as non-fall.
(3) *True negative*: recognize non-fall activities correctly.
(4) *False positive*: recognize non-falls as a fall.

Figure 8 demonstrated that the algorithm *PosTra* can improve the falls detection accuracy significantly in both aspects: true positives (real falls) and true negatives (non falls) compared to the algorithm *AccThr*. For example, *PosTra* was able to correctly recognize the two types of falls: *Fall-lying* and *Fall-sitTilted* (95 % and 93 % true positives respectively). Nevertheless, *AccThr* was only able to detect the *Fall-lying* correctly (92 % true positive), it is false for the Fall-sitTilted (96 % false negatives), since no large acceleration occurred when falls ending with sit-tilted.

For the fall-like activities, compared to AccThr, *PosTra* can exclude most of the jumping (90 % vs. 50 % true negative), sit down heavily (96 % vs. 15 % true negative), and normal lying (87.5 % vs. 4 % true negative), however the true negative for bending was 50 % vs. 75 %.

The algorithm *PosTra* will trigger the music alert (possible falls) to wait for users pressing the stop button in the below cases:

- When the sitting period of time is less than 2 seconds before the normal lying.
- When bending is more than 70°. Since the phone's orientation (or the features of the acceleration and orientation angles) is similar for both postures "deep waist bend" and lying.
- When the posture is keeping sit-tilt on a chair after the jumping.

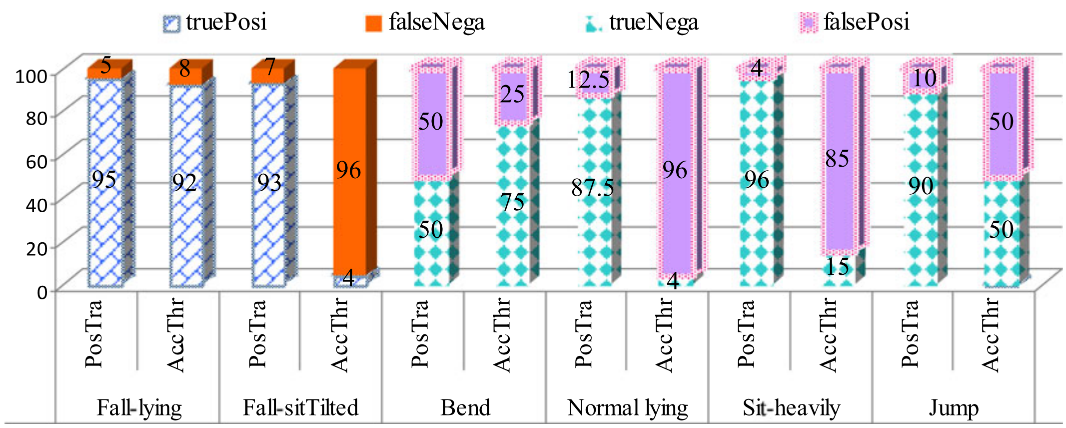


Fig. 8 Comparison of experimental results between algorithms *PosTra* and *AccThr*

Fig. 9 Comparison of two normal lying, one is sitting more than 2 s before the lying; another is sitting less than 2 seconds before the lying

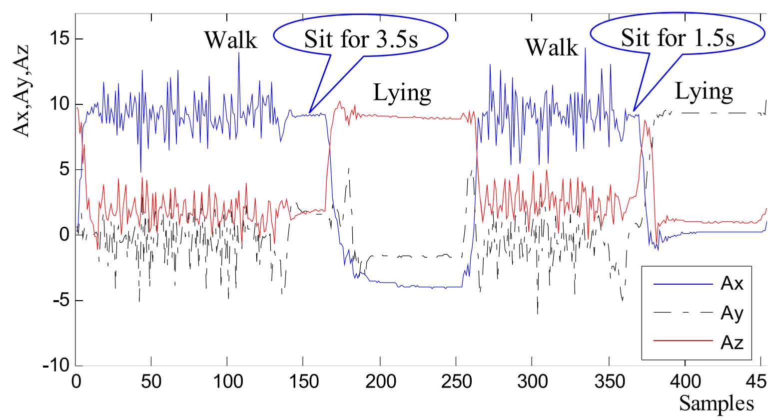


Figure 9 illustrates the limitations for algorithms *PosTra* and *AccThr* for the two ways normal lying. Whatever lying posture all will cause a large acceleration changing, hence *AccThr* got 4 % *true negative* for all normal lying. *PosTra* detect falls based on the posture transition and current time as well as position, however, if the sit period of time is less than 2 seconds (such as 1.5 s as shown in Fig. 9) before the lying, then this sit posture will be ignored based on the motionless rule R_{ML} defined in this study. Thus the normal posture transition from sit to lying was analyzed as from walk to lying (abnormal posture transition), hence it was detected as a fall.

5 Conclusion and future work

The innovations in this paper are: (1) the motion and motionless postures were classified using a hierarchal rule-based algorithm, based on principles of accelerometer and orientation sensors as well as the kinematical theory, it is reliable for different subjects and different situations, and also trustworthy for elder daily activity monitoring in real life, since it is not only based on empirical thresholds or subject-based training models; (2) the fall detection was implemented by analyzing whether the current lying and sit-tilted posture are normal or abnormal, based on the posture transition analysis with current time and users' current position; (3) a music based alert with a stop button will appear if a possible fall is raised (unexpected lying or sit-tilted), and finally, a fall or a normal lying/sit-tilted will be determined according to whether the user stops the alert music.

Experimental results demonstrate that the approach can correctly detect various falls efficiently (real-time within a smart phone) and also avoid most false positives and false negatives. Experiments were performed in various situations such as fall quickly on the ground, fall slowly onto the bed, falls ending with a lying or sit-tilted posture, in addition to the normal lying, at a real home environment. More activity postures and falls situations such as moving up/down stairs, cycling, and driving and running will be addressed in the future work.

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